Leveraging Load Migration and Basestaion Consolidation for Green Communications in Virtualized Cognitive Radio Networks

Xiang Sheng, Jian Tang, Chenfei Gao, Weiyi Zhang and Chonggang Wang

***Abstract*—With wireless resource virtualization, multiple Mobile Virtual Network Operators (MVNOs) can be supported over a shared physical wireless network and traffic loads in a Base Station (BS) can be easily migrated to more power-efficient BSs in its neighborhood such that idle BSs can be turned off or put into sleep to save power. In this paper, we propose to leverage load migration and BS consolidation for green communications and consider a power-efficient network planning problem in virtualized Cognitive Radio Networks (CRNs) with the objective of minimizing total power consumption while meeting traffic load demand of each MVNO. First, we present a Mixed Integer Linear Programming (MILP) to provide optimal solutions. Then we present a general optimization framework to guide algorithm design, which solves two subproblems, channel assignment and load allocation, in sequence. For channel assignment, we present a ($\frac{1}{\Delta}$)-approximation algorithm (where Δ is the maximum number of BSs a BS can potentially interfere with). For load allocation, we present a polynomial-time optimal algorithm for a special case where BSs are power-proportional as well as two effective heuristic algorithms for the general case. In addition, we present an effective heuristic algorithm that jointly solves the two subproblems. It has been shown by extensive simulation results that the proposed algorithms produce close-to-optimal solutions, and moreover, achieve over 45% power savings compared to a baseline algorithm that does not migrate loads or consolidate BSs.**

***Index Terms*—Green wireless communications, virtualization, cognitive radio, basestation consolidation, load migration.**

I. Introduction

Due to fast growth of wireless users and their communication demands, wireless networks have become one of major contributors for power consumption. Recent studies [8] have shown that there are currently more than 4 million Base Stations (BSs), each of which consumes an average of 25MWh per year. The number of BSs in developing regions are expected to double by 2012. Such huge energy consumption has raised public concerns about electricity costs, and greenhouse gas emissions that are known to have a negative impact on global climate. Therefore, the problem of how to build a green (power-efficient) wireless network has attracted extensive research attention from both industry and academia recently. There is significant potential for power savings in wireless networks. Most previous research efforts, however, were mainly focused on reducing energy consumption of battery powered wireless devices such as mobile phones and sensor nodes. Research attention has not been well paid to power savings on BSs until very recently. The most straightforward way to reduce power consumption of BSs is to turn off idle BSs or put them into sleep. However, without careful network planning, turning off BSs might lead to loss of coverage and unsatisfied traffic demands.

Virtualization is the creation of a virtual (rather than actual) version of certain physical resources, such as a computer, storage device, or network resources. Virtualization has emerged as a useful technology for improving resource utilization and power efficiency. For example, in a virtualized data center, Virtual Machines (VMs) can be created to host applications and servers can be consolidated by migrating VMs such that idle servers and chassis, can be shut down or put into sleep. Virtualization technology has been introduced to wireless networking recently [11]. In general, network virtualization enables deploying customized services and resource management solutions in isolated slices on a shared physical network. Particularly, with wireless resource virtualization, multiple Mobile Virtual Network Operators (MVNOs) can be supported over a shared physical wireless network and traffic loads in a BS can be easily migrated to more power-efficient BSs in its neighborhood such that idle BSs can be turned off or put into sleep to save power.

Emerging Cognitive Radio (CR) technology and the Dynamic Spectrum Access (DSA) approach [2] enable unlicensed wireless users (a.k.a secondary users) to sense and access the under-utilized spectrum opportunistically even if it is licensed. CRs have been considered as the next generation wireless communication technology that can lead to better spectrum utilization and higher network capacity.

In this paper, we propose to leverage load migration and BS consolidation for green communications and consider a power-efficient network planning problem in virtualized Cognitive Radio Networks (CRNs) with the objective of minimizing total power consumption while meeting traffic load demand of each MVNO. We find that the problem can divided into two subproblems: the channel assignment problem and the load allocation problem. The channel assignment problem seeks a solution that assigns a channel for each BS in an interference-free manner. The load allocation problem is to determine which subset of BSs to turn off (or put into sleep) and how to allocate load of each MVNO on every BS to active BSs. Power savings can be achieved by migrating loads of MVNOs to more power-efficient BSs and/or shutting down BSs to save idle power. Note that since different CR BSs work on different channels, their power efficiency might be different because to maintain certain transmission range, the BS using a low-frequency channel can use less power than that using a high-

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frequency channel due to the signal propagation property. We summarize our contributions in the following:

1) We formally define a BS consolidation problem and present an Mixed Integer Linear Programming (MILP) formulation to provide optimal solutions.

2) We present a general optimization framework to guide algorithm design, which solves two subproblems, channel assignment and load allocation, in sequence. We present a channel assignment algorithm with an approximation ratio of $(\frac{1}{\Delta})$ (where Δ is the maximum number of BSs a BS can potentially interfere with).

3) For the load allocation problem, we present a polynomial-time optimal algorithm for a special case where BSs are power-proportional as well as two fast heuristic algorithms for the general case.

4) It has been shown by extensive simulation results that the proposed algorithms produce close-to-optimal solutions, and moreover, achieve over 45% power savings compared to a baseline algorithm that does not migrate loads or consolidate BSs.

Even though green wireless networking has attracted extensive attention recently, most previous works were focused on 3G/4G/WiFi networks (rather than CRNs) without addressing the case where there are multiple MVNOs in the network. To the best of our knowledge, we are the first to propose to leverage load migration and BS consolidation for green communications in a virtualized CRN (with multiple MVNOs), and present theoretically well-founded and practically efficient algorithms to solve the corresponding optimization problems.

II. Related Work

Even though server/desktop virtualization has been well studied, research on wireless resource virtualization is still in its infancy. In [11], Kokku *et al.* described the design and implementation of a Network Virtualization Substrate (NVS) for effective virtualization of wireless resources in cellular networks. NVS meets three key requirements: isolation, customization, and efficient resource utilization. They demonstrated its efficacy via a prototype implementation and evaluation on a WiMAX testbed. In [17], the authors proposed a Cognitive Virtualization Platform called AMPHIBIA, which enables end-to-end slicing over wired and wireless networks and exploits the network advantages of virtualization and CR technologies. In [33], Zhu *et al.* introduced the first TDD WiMAX Software Defined Radio (SDR) BS implemented on a commodity server, in conjunction with a novel design of a remote radio head. In [13], the authors presented a software-defined cellular network architecture that supports flexible slicing of network resources. Wireless resource virtualization has also been studied for LTE networks [31], WiMAX networks [3], WiFi networks [28], access networks [12], multihop wireless networks [30], and wireless sensor networks [10].

Green wireless communications and networking, especially power efficiency on BSs and wireless infrastructure, has received research attention recently. In [20], Peng *et al.* proposed a profile-based approach to green cellular infrastructure, which leverages temporal-spatial traffic diversity and node deployment heterogeneity, and powers off under-utilized BSs based on historical data. The authors of [6] provided an algorithm that minimizes power consumption by selectively turning on or off cell towers and deciding which power to assign to the active ones and what frequencies to use, so as to maintain full coverage and respect users' capacity demands. In [4], the authors studied the effect of cell sizes on the energy consumption and proposed a practical, 2-level scheme that adjusts cell sizes between two fixed values, and showed an energy saving of up to 40%. In [23], the authors first studied how to adaptively vary the processing speed based on incoming load, and then proposed and analyzed a distributed algorithm, called Speed Balance, that can yield significant energy savings. In [5], Elayoubi *et al.* investigated network sleep mode for reducing energy consumption of radio access networks. They proposed an offline-optimized controller that associates traffic with an activation/deactivation policy that maximizes a multiple objective function of QoS and energy consumption. In [14], the authors showed how to optimize the energy saving, first assuming that any fraction of cells can be turned off, and then accounting for the constraints resulting from the cell layout. A comprehensive survey on this topic can be found in [8].

Spectrum sharing in CRNs has been extensively studied. In [2], Akyildiz *et al.* presented a comprehensive survey of issues and solutions in CRNs. Tang *et al.* introduced a Multi-Channel Contention Graph (MCCG) to characterize the impact of interference and proposed joint scheduling and spectrum allocation algorithms based on MCCG in [24]. In [27], Wang *et al.* presented a joint power/channel allocation scheme that uses a distributed pricing strategy to improve network performance. In [32], the authors derived optimal and suboptimal distributed spectrum sense and access strategies for the secondary users under a framework of Partially Observable Markov Decision Process (POMDP). Three opportunistic spectrum access schemes using different sensing, back-off and transmission mechanisms were presented in [9]. A dynamic game approach was proposed in [19] to solve the problem of spectrum sharing among a primary user and multiple secondary users. In another well-cited work [18], a game theoretic framework was proposed to analyze the behavior of CRs for distributed adaptive channel allocation.

The differences between our work and these related works are summarized as follows: 1) Unlike most papers on wireless resource virtualization which were mainly focused on how to design and implement resource virtualization at one node, we aim to leverage load migration and BS consolidation (that can be enabled by virtualization) for reducing power consumption of the whole network 2) Most previous works on green wireless networking studied power-efficient resource management problems in the context of 3G/4G/WiFi networks rather than CRNs and did not address the case where there are multiple MVNOs in the network. 3) Different from most works on spectrum sharing in CRNs which aimed at improving spectrum utilization and network capacity, we study a power-efficient network planning problem in the context of a network with virtualized CR BSs, which has never been done before.

III. Problem Definition

We summarize major notations in the following table for quick reference.

TABLE I
MAJOR NOTATIONS

Variable	Description
A_i	Idle power
B_i^f	The load coefficient in the power consumption function of BS i
C_i^h	The capacity of BS i on channel h
H_i	A set channels available to BS i
$H_{\max}$	The maximum number of available channels on a BS
K	The number of MVNOs
L_{ik}	The load demand of MVNO k on BS i
l_i	The total traffic load on BS i
N	The number of BSs
S_i	The neighbor set of BS i
I_i	The interference set of BS i
x_i	Decision variable: $x_i = 1$ if BS i is turned on; 0, otherwise.
y_i^h	Decision variable: $y_i^h = 1$ if channel h is assigned to BS i; 0, otherwise.
l_{ik}^{jh}	Decision variable: The amount of load of MVNO k on BS i that is migrated to BS j on channel h.

In this paper, we consider a CRN with N BSs, which is shared by K MVNOs. The available spectrum is divided into a set of orthogonal *channels*. Note that since we study a network planning problem rather than a MAC layer channel selection problem, the channel considered here represents a relatively large portion of the spectrum and may include a group of sub-channels defined in the context of OFDMA. There are a set H_i of channels available to each BS i, which may change over time. Channel availability information can be obtained from a spectrum database (as suggested by FCC) or using a spectrum sensing method [29]. Since available channels of a CR may be distributed over a large range of spectrum, they may have (or be able to support) quite different properties such as channel gain, data rate, etc. Each BS is assigned one channel to support wireless users of multiple MVNOs for a certain period of time.

With virtualization, wireless resources (such as timeslots in an OFDMA frame) are allocated dynamically to slices, each of which may correspond an MVNO or a group of service flows of an MVNO. In a BS, a slice manager [11] (similar to hypervisor in the context of server virtualization) can be used to manage resource allocation for slices with the goal of achieving isolation, customization and efficient utilization of resources. Each MVNO provides wireless communication services for a group of mobile users, which create certain traffic loads on each BS. We use a $N \times K$ matrix L to specify the traffic load of MVNO k on BS i. Each BS i can migrate part of or all of its traffic load to a set S_i of neighboring BSs. With virtualization, a BS can quickly adjust resource allocation for its slices to accommodate traffic loads migrated from other BSs. Different (conservative or aggressive) criteria can be used to identify such a neighbor set for each BS. Note that $i \in S_i$. In addition, for each BS i, there is a set of BSs I_i which can potentially interfere with BS i if they work on the same channel. If channel h is assigned to BS i, then any BS in I_i cannot be assigned channel h. Similarly, different criteria can be used to identify such an interference set for each BS. Note that $i \notin I_i$ (this is just a technical agreement for easy presentation). In the simulation, we used relatively conservative methods to identify these two sets for each BS, which will be explained in Section VI.

Similar as in [20], we adopt a simple and widely-used linear model for power consumption of a BS i, which is given as follows:

$$P_i(l_i, f) = A_i + B_i^f * l_i, \tag{1}$$

where A_i is a constant that specifies the idle power usage, l_i is the traffic load, and B_i^f is the load coefficient. Note that the value of this coefficient may vary with transmission frequency f because usually low-frequency wireless signals travel longer than high-frequency signals if transmitted at a given power level, in other words, to maintain certain transmission range, the BS using a low-frequency channel can use less power than that using a high-frequency channel. However, the values may be the same for multiple channels on a common spectrum band. The values of A_i and B_i^f can be obtained via a profile-based approach such as that in [20] or estimated using a signal propagation model [21]. We say a BS is *power-proportional* if $A_i = 0$. Currently, almost no BS is power-proportional. However, we still consider this special case since with the advancement of communication hardware and cooling technology, it might be possible to significantly reduce idle power to make it close to zero in the future.

We are interested in finding a resource allocation solution that specifies which channel to be assigned to each BS and how to allocate traffic loads of each MVNO. A resource allocation solution is said to be *feasible* if available channels are assigned to BSs in a interference-free manner, the traffic load demands specified by the matrix L can be satisfied and the total load on each BS does not exceed its capacity. Now, we are ready to define the optimization problem.

Definition 1: Given N BSs, K MVNOs, a $N \times K$ traffic load matrix L and the set H_i of available channels on each BS $i, i \in \{1, \cdots, N\}$, a power-efficient network planning problem seeks a feasible resource allocation solution that minimizes the total power consumption of BSs.

Note that this network planning procedure can be conducted on a relatively large time scale, e.g., 30 minutes or 1 hour. In addition, we are only interested in finding out how to distribute traffic loads of MVNOs among BSs in a network, however, how to allocate resources to slices to support multiple MVNOs to meet their load demands in a single BS is out of scope of this paper, but has been studied in [11], [13], [31].

This optimization problem is very hard to solve since its subproblem, interference-free channel assignment, is known to be NP-hard [24]. Therefore, we first present an MILP formulation to provide optimal solutions.

Decision variables:

- $x_i = \{0, 1\}$: $x_i = 1$ if BS i is turned on; 0, otherwise.
- $y_i^h = \{0, 1\}$: $y_i^h = 1$ if channel h is assigned to BS i; 0, otherwise.

- $l_{ik}^{jh} \geq 0$: The amount of load of MVNO k on BS i that is migrated to BS j on channel h.

MILP-Green

$$\min_{\langle x_i, y_i^h, l_{ik}^{jh} \rangle} \sum_{i=1}^{N} (A_i x_i + \sum_{h \in H_i} B_i^h (\sum_{k=1}^{K} \sum_{j: i \in S_j} l_{jk}^{ih})) \tag{2}$$

Subject to:

$$\sum_{h \in H_i} y_i^h \leq x_i, \quad \forall i \in \{1, \cdots, N\}; \tag{3}$$

$$y_i^h + \frac{\sum_{j \in I_i} y_j^h}{N} \leq 1, \quad \forall i \in \{1, \cdots, N\}, \quad \forall h \in H_i \tag{4}$$

$$\sum_{j \in S_i} \sum_{h \in H_j} l_{ik}^{jh} = L_{ik}, \quad \forall i \in \{1, \cdots, N\}, \quad \forall k \in \{1, \cdots, K\}; \tag{5}$$

$$\sum_{k=1}^{K} \sum_{j: i \in S_j} l_{jk}^{ih} \leq y_i^h C_i^h, \quad \forall i \in \{1, \cdots, N\}, \quad \forall h \in H_i. \tag{6}$$

In this formulation, the objective (2) is to minimize total power consumption of BSs. By abusing the notation a little bit, we use h to denote both channel h and its central frequency. As described before, each BS can only be assigned one channel, which is guaranteed by constraints (3). Constraints (4) ensure that channels are assigned in an interference-free manner, i.e., if channel h is assigned to BS i, then none of BSs in the interference set I_i can be assigned this channel. Each MVNO k has a load demand L_{ik} on each BS i, which must be satisfied by using BS i and/or BSs in the neighbor set S_i via load migrations. This is ensured by constraints (5). The last set of constraints (6) make sure that each BS i has sufficient capacity to support its own traffic loads and those migrated from neighboring BSs. Note that the capacity of a BS can be conservatively set to certain percentage of its actual capacity to guarantee quality of service since it may need to serve loads migrated from neighboring BSs. It is known that solving such an MILP may take exponentially long time, especially for large cases. Hence, we present polynomial-time algorithms in the next section.

IV. Optimization Framework

In this section, we first present a 2-step framework to guide algorithm design. Essentially, the optimization problem defined above consists of two subproblems: *channel assignment and load allocation*. The channel assignment subproblem is to determine which channel to be assigned to each BS. The load allocation subproblem is to determine which subset of BSs should be turned on and how to distribute loads to active BSs. We formally present the optimization framework in the following.

It is important to obtain a channel assignment that can (hopefully) lead to a minimum power solution to the original problem. Our approach is to set a weight for each channel h on BS i, $w(i,h) = \frac{C_i^h}{P_i(C_i^h, h)}$, where C_i^h is the capacity of BS i on channel h and $P_i(C_i^h, h)$ gives the total power needed to support C_i^h amount of loads on BS i with channel h. Therefore this weight function returns per-watt load that can be supported by assigning channel h to BS i. By finding a channel assignment with maximum total weight, we can (hopefully) have sufficient capacity to accommodate traffic loads with low power consumption. In Step 2, an algorithm can be used to obtain a load allocation based on the channel assignment computed in Step 1.

Algorithm 1 The Optimization Framework

Step 1	Compute a channel assignment that maximizes the total weight (defined below) of assigned channels;
Step 2	Based on the channel assignment, obtain a minimum-power load allocation.

Next, we present an approximation algorithm for channel assignment. For the load allocation problem, we present a polynomial-time optimal algorithm for a special case where BSs are power-proportional as well as two fast heuristic algorithms for the general case.

A. Channel Assignment Algorithm

The channel assignment problem is to determine a channel assignment that can result in the maximum total weight (defined above) and ensures that any two BSs that interfere with each other are given two different channels. To assist computation, we construct an auxiliary graph, the Multi-Channel Contention Graph (MCCG), to model conflict (interference) in a network with multiple heterogeneous channels, which was proposed in our previous work [24]. To ensure the completeness of the presentation, we briefly describe how it is constructed. In an MCCG $G_C(V_C, E_C)$, every vertex corresponds to a BS-channel pair in $\mathcal{A}$, where $\mathcal{A} = \{(i,h) : \forall i \in \{1, \cdots, N\}, \forall h \in H_i\}$. There is an undirected edge connecting two vertices in V_C if their corresponding BS-channel pairs *interfere* with each other. Two BS-channel pairs (i,h) and (j,h') are said to interfere with each other if 1) $i = j$ or 2) $h = h'$ and ($j \in I_i$ or $i \in I_j$), where I_i and I_j are the interference sets of BS i and j respectively. Note that there is an undirected edge between every two vertices corresponding to BS-channel pairs that contain a common BS because they always conflict with each other no matter which channel is considered since a BS can only work on one channel. In other words, all vertices corresponding to a common BS form a clique in G_C. This case is covered by the first condition. Now, we are ready to present the channel assignment algorithm.

Every time, the algorithm selects a vertex (BS-channel pair) with the maximum weight-to-degree ratio and assigns the channel accordingly. In this way, vertices with high weights and low interference impact are expected to be selected for channel assignment. We analyze the performance and time complexity of this algorithm in the following.

Theorem 1: Algorithm 2 is a $\frac{1}{\Delta}$-approximation algorithm for the channel assignment problem (where Δ is the maximum vertex degree on the MCCG) and has a time complexity of $O(N^2 H_{\max})$ (where $H_{\max}$ is the maximum number of available channels on a BS).

Algorithm 2 The Channel Assignment Algorithm

Step 1 $V := V_C$; Set all $\langle y_i^h \rangle$:=0;
Step 2 **while** $(V \neq \emptyset)$
$v_{\max} := \text{argmax}_{v \in V} \frac{w(v)}{\Delta_v + 1}$, where Δ_v is the degree
of vertex v on G_C;
$y_{i_{\max}}^{h_{\max}} := 1$, where $v_{\max} = (i_{\max}, h_{\max})$;
$V := V - V_{\max}$, where $V_{\max}$ is the set of vertices share a common edge with $v_{\max}$;
endwhile
Step 3 **return** $\langle y_i^h \rangle$;

Proof: Due to the way how the MCCG is constructed, the channel assignment problem can be transformed to the maximum weight independent set problem on an MCCG. It has been shown in [22] that a greedy algorithm that selects a vertex with the maximum weight-to-degree ratio has an approximation ratio of $\frac{1}{\Delta}$ for the maximum weight independent set problem. Hence, our algorithm offers the same approximation ratio for the channel assignment problem.

Every time, it takes $O(NH_{\max})$ to assign channel for one BS. Hence, the overall time complexity of the proposed algorithm is $O(N^2 H_{\max})$. This completes the proof. ■

B. Load Allocation Algorithms

After the channel assignment is determined, we can solve the load allocation subproblem. First, we construct a directed auxiliary graph $G_f(V_O \bigcup V_B \bigcup \{s, z\}, E_f)$ to assist computation. In this graph, each vertex $u \in V_O$ corresponds to a BS-MVNO pair (i, k) and each pair of vertices $v_j^{in}, v_j^{out} \in V_B$ correspond to a BS j. There is a directed edge from each vertex $u = (i, k) \in V_O$ to $v_j^{in} \in V_B$ (corresponding to BS j) if $j \in S_i$, where S_i is the neighbor set of BS i defined above. The cost and capacity of such an edge e are set to $w_e = 0$ and $C_e = \infty$ respectively. Moreover, there is a directed edge from each $v_j^{in} \in V_B$ to $v_j^{out} \in V_B$, whose cost and capacity are set to B_j^h and C_j^h respectively. where B_j^h is the load coefficient in the power consumption function of BS j and C_j^h is the capacity of BS j when using assigned channel h. In addition, we create a virtual sink z and there is a directed edge from each $v_j^{out} \in V_B$ to z, whose cost and capacity are set to 0 and ∞ respectively. We also create a virtual source s and there is a directed edge from s to each $u \in V_O$, whose cost and capacity are set to 0 and L_{ik} respectively.

Next, we use an example in Fig. 1 to show how to construct this graph. In this example, we have 2 MVNOs and 4 BSs which are assigned channels 1, 2, 3 and 4 respectively. In addition, both neighbor sets S_1 and S_2 include BSs 1 and 2.

With this auxiliary flow graph, the load allocation problem can be transformed to a min-cost flow problem in this graph. Specifically, for the power-proportional case where the power consumption of each BS i is $B_i^h * l_i$, then there is no need to turn off any BS and the load allocation problem becomes a traditional min-cost flow problem [1], which can be formulated as the following LP problem, in which f_e specifies the amount of flow over edge e.

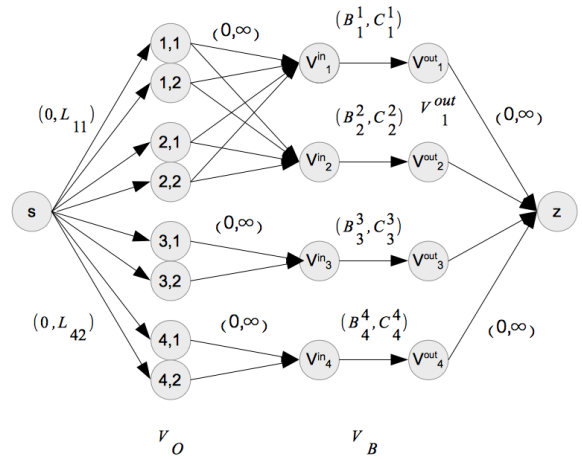

Fig. 1. An auxiliary flow graph

LP-Flow-PP:

$$\min_{\langle f_e \rangle} \sum_{e \in E} w_e f_e \tag{7}$$

$$\sum_{e \in E_s^{out}} f_e = L_{total}; \tag{8}$$

$$\sum_{e \in E_v^{in}} f_e = \sum_{e \in E_v^{out}} f_e, \quad \forall v \in V_O \bigcup V_B; \tag{9}$$

$$f_e \leq C_e, \qquad \forall e \in E_f. \tag{10}$$

In the formulation, w_e and C_e are the cost and capacity of edge e respectively. E_v^{out} and E_v^{out} are the set of edges going out from v and into v respectively. L_{total} is the total load of all MVNOs, i.e., $L_{total} = \sum_{i=1}^{N} \sum_{k=1}^{K} L_{ik}$. We present an algorithm for this special case of load allocation problem in the following.

Algorithm 3 The Min-Cost-Flow-Based Load Allocation Algorithm for the Power-Proportional Case

Step 1 Construct the auxiliary flow graph G_f;
Step 2 Find a min-cost $s - t$ flow allocation $\langle f_e \rangle$ on G_f by solving the LP-Flow-PP;
Step 3 **forall** $e = (u, v_j^{in})$, where $u = (i, k) \in V_O$ and $v_j^{in} \in V_B$
$L_{ik}^{jh} = f_e$, where h is the channel assigned to BS j;
endforall
return $\langle L_{ik}^{jh} \rangle$.

Theorem 2: The min-cost-flow-based algorithm optimally solves the power-proportional case of the load allocation problem in polynomial time.

Proof: Constraint (8) ensures the total amount of $s - t$ flow is equal to the total load demand. Since the capacity of each link e going out from s to $u = (i, k) \in V_O$ is set to $C_e = L_{ik}$, constraint (8) ensures the load demand of each MVNO k on every BS i is satisfied. Moreover, due to the way how the capacity of each link e between $v_j^{in}, v_j^{out} \in V_B$ is set (i.e., $C_e = C_j^h$), constraints (10) make sure that each BS j

has sufficient capacity to support all loads allocated to it. The objective function (7) minimizes the total cost of flow, which is equivalent to minimizing the total power consumption since the costs of all edges are set to 0 except that those between $v_j^{in}, v_j^{out} \in V_B$ are set to the load coefficient B_i^h of the power consumption function.

This LP problem has no more than $(N(K+2)+N^2K)$ variables and no more than $(2N(K+2)+N^2K+1)$ constraints since G_f has $(N(K+2)+2)$ vertices and no more than $(N(K+2)+N^2K)$ edges. Hence, it can be solved in polynomial time. This completes the proof. ■

For the general case where there is a non-zero idle power for each BS, the load allocation problem can also be formulated as another flow problem on G_f, in which f_e specifies the amount of flow over edge e; and z_e is an integer decision variable that indicate if edge e is activated ($z_e = 1$) or not ($z_e = 0$).
MILP-Flow:

$$\min_{\langle f_e, z_e \rangle} \sum_{e \in E} (a_e z_e + w_e f_e) \tag{11}$$

$$\sum_{e \in E_s^{out}} f_e = L_{total};$$

$$\sum_{e \in E_v^{in}} f_e = \sum_{e \in E_v^{out}} f_e, \quad \forall v \in V_O \bigcup V_B;$$

$$f_e \le z_e C_e, \quad \forall e \in E_f^{intra}; \tag{12}$$

$$f_e \le C_e, \quad \forall e \in E_f \setminus E_f^{intra}. \tag{13}$$

In this formulation, E_f^{intra} is the set of edges between $v_j^{in}, v_j^{out} \in V_B$, $j \in \{1, \cdots, N\}$. $a_e = A_j$ for $e \in E_f^{intra}$ (corresponding to BS j) and $a_e = 0$ for all the other edges. $z_e = 0$ indicates that the corresponding BS is turned off. The objective (11) is to minimize total power consumption based on the general power consumption model with non-zero idle power. Unlike the power-proportional case, the flow problem presented above is known to be the Fixed Charge Network Flow (FCNF) problem [16] that has been shown to be NP-hard. So we can only have polynomial-time heuristic algorithms that give suboptimal solutions. We present an algorithm for the general load allocation problem in the following.

Algorithm 4 The Bilinear Relaxation Based Algorithm

Step 1 Construct the auxiliary flow graph G_f.
Step 2 Solve the problem specified by the MILP-Flow using the bilinear relaxation based algorithm in [16].
Step 3 **forall** $e = (u, v_j^{in})$, where $u = (i,k) \in V_O$ and $v_j^{in} \in V_B$
  $L_{ik}^{jh} = f_e$, where h is the channel assigned to BS j;
  endforall
  return $\langle L_{ik}^{jh} \rangle$.

To the best of our knowledge, the bilinear relaxation based algorithm presented in [16] is the best algorithm for the FCNF problem. The basic idea of this algorithm is to approximate the objective function of the FCNF problem by a piecewise linear one, and construct a Concave Piecewise Linear Network Flow (CPLNF) problem (which can be formulated as an LP problem and solved in polynomial time). A proper choice of parameters in the CPLNF problem can guarantee the equivalence between these two problems. Solving the FCNF problem needs to solve a sequence of CPLNF problems. The algorithm in [16] employs the the bilinear relaxation based algorithm presented in [15], to find a solution to a CPLNF problem. More details can be found in [15] and [16].

We also present a simple algorithm, the *iterative shutdown* algorithm, to solve the load allocation problem without constructing the auxiliary flow graph.

Algorithm 5 The Iterative Shutdown Algorithm

Step 1 $R = \{1, \cdots, N\}$;
  Set $l_i := \sum_{k=1}^{K} L_{ik}, \forall i \in \{1, \cdots, N\}$;
Step 2 **while** (1)
  $j_{\min} := \text{argmin}_{j \in R} \frac{l_j}{|S_j \bigcap R|}$;
  $R := R - \{j_{\min}\}$;
  Solve LP-Load(R);
  if (No feasible solution) **or** (total power increases)
    $R := R + \{j_{\min}\}$;
    break;
  endif
  Update $l_i := \sum_{k=1}^{K} \sum_{j: i \in S_j \bigcap R} l_{jk}^i$,
  $\forall i \in \{1, \cdots, N\}$ where $\langle l_{jk}^i \rangle$ is
  the solution returned by solving the LP-Load;
endwhile
Step 3 **return** R and $\langle l_{ik}^j \rangle$.

LP-Load(R)

$$\min_{\langle l_{ik}^j \rangle} \sum_{i \in R} (A_i + B_i (\sum_{k=1}^{K} \sum_{j: i \in S_j \bigcap R} l_{jk}^i)) \tag{14}$$

Subject to:

$$\sum_{j \in S_i \bigcap R} l_{ik}^j = L_{ik}, \quad \forall i \in \{1, \cdots, N\}, \quad \forall k \in \{1, \cdots, K\}; \tag{15}$$

$$\sum_{k=1}^{K} \sum_{j: i \in S_j \bigcap R} l_{jk}^i \le C_i, \quad \forall i \in \{1, \cdots, N\}. \tag{16}$$

In the algorithm, R and l_i keep track of the set of active BSs and the load of each BS i respectively. The algorithm keeps trying to turning off a BS until not possible. Every time, a BS j_{min} with smallest load-to-neighbor-number-ratio is selected and the LP-Load is used to test if a feasible load allocation can still be found by shutting down BS j_{min}. The algorithm makes such a selection because it is likely that such a BS can be shut down and its load can be migrated to other active BSs in its neighborhood. The LP-Load is similar to the MILP-Green except that it does not include channel assignment variables y_i^h and the related constraints. Here the superscript h is removed from load allocation variables $\langle i_{jk}^{ih} \rangle$ since the channel assignment is given as input for this algorithm.

V. Joint Algorithm

In this section, we present an effective algorithm to jointly solve the channel assignment and load allocation problems. The basic idea of this algorithm is to deal with BS one by one in the descending order of their traffic demands and every time, try to find a feasible load allocation and channel assignment that can lead to minimum power consumption without changing the existing decisions. The algorithm is formally presented as follows.

Algorithm 6 The Joint Algorithm

Step 1 Sort all the BSs in the descending order of its loads and store the sorted list in Q;
$R := \emptyset$;
Set all $\langle \hat{C}_j \rangle := 0$;
Set all $\langle y_i^h \rangle := 0$;

Step 2 **forall** $i \in Q$
  Solve LP-Load-Local$(i, R, \langle \hat{C}_j \rangle)$
  if (Found a feasible solution $\langle l_{ik}^j \rangle$)
    $\hat{C}_j := \hat{C}_j - \sum_{k=1}^{K} l_{ik}^j, \forall j \in S_i \bigcap R$;
    continue;
  endif
  $R := R + \{i\}$;
  $h_{\min} = \text{argmin}_{h \in H_i}$LP-Load-Local$(i, R, \langle \hat{C}_j \rangle)$,
  where $\langle \hat{C}_j \rangle := \langle C_j^h \rangle$;
  if (None of LP-Load-Local returns a feasible solution)
    return FAILED;
  endif
  $y_i^{h_{\min}} := 1$;
  $H_j := H_j - \{h_{\min}\}, \forall j \in I_i$;
  $\hat{C}_j := \hat{C}_j - \sum_{k=1}^{K} l_{ik}^j, \forall j \in S_i \bigcap R$;
endforall

Step 3 **return** $\langle y_i^h \rangle$, R, $\langle l_{ik}^j \rangle$.

LP-Load-Local $(i, R, \langle \hat{C}_j \rangle)$

$$\min_{\langle l_{ik}^j \rangle} \sum_{j \in S_i \bigcap R} (A_j + B_j \sum_{k=1}^{K} l_{ik}^j) \tag{17}$$

Subject to:

$$\sum_{j \in S_i \bigcap R} l_{ik}^j = L_{ik}, \quad \forall k \in \{1, \cdots, K\}; \tag{18}$$

$$\sum_{k=1}^{K} l_{ik}^j \leq \hat{C}_j, \qquad \forall j \in S_i \bigcap R. \tag{19}$$

In this algorithm, R keeps track of the set of BSs which has been determined (by the algorithm) to power on. $\hat{C}_j$ gives the residual capacity of BS j. $\langle l_{ik}^j \rangle$ specify load allocation and superscript h is removed since the channel assignment of BS in R have already been determined. The algorithm goes through the BS list in the descending of their demands. Every time, the algorithm deals with only one BS. It first check if all its traffic loads can be migrated to BSs in $S_i \bigcap R$ by solving the LP-Load-Local. If so, BS i will be turned off and its load will be migrated to its active neighboring BSs. The algorithm examines this option first because the idle power usually contributes significantly to the total power usage of a BS (over 50% in most cases), therefore, it is desirable to shut it down if at all possible. Otherwise, the algorithm turns on this BS and finds a channel assignment that can lead to minimum power consumption as well as a load allocation using the same LP. This is a greedy algorithm which makes on/off, channel assignment, and load allocation decisions for a BS in one iteration and will not change them in the following iterations.

The first step of the algorithm can be done in $O(N \log N)$ time. In the 2nd step, even though the LP-Load-Local needs to be solved $O(NH_{\max})$ times, where $H_{\max}$ is the maximum number of available channels on a BS, the LP only includes a small number of variables and constraints since this LP only involves the neighbors of the BS in question. Hence, it can be solved very efficiently.

VI. Simulation Results

In the simulation, the target region was chosen as a square area with a size of 15×15 km^2. N BSs were randomly placed in the region, whose locations follow a two-dimensional uniform distribution. The effective/maximum transmission ranges were set to $r = 2$km and $r_{\max} = 2r = 4$km, which are quite typical in a cellular network [20]. Similar as in [20], the neighbor set of BS i was defined as $S_i = \{j : d(j,i) \leq (r_{max} + r), j \in \{1, \cdots, N\}\}$. We used a relatively conservative method to define the interference set I_i of BS i as $I_i = \{j : d(j,i) \leq 2r_{max}, j \in \{1, \cdots, N\}\} - \{i\}$.

The total number of available channels was set to 50 and each channel has a bandwidth 50MHz. They were evenly distributed in a portion of spectrum centered at 2GHz. In the simulation, 15 Primary Users (PUs) were randomly placed in the target area. Each PU randomly chose one channel to use. If the distance between a PU and a CR BS is less than the interference range $2r_{\max} = 8$km, then the CR BS cannot be assigned the channel used by the PU. As described above, the capacity of a BS depends on the channel assigned to it. Similar as in [4], the capacity of a BS using the channel at 2GHz was set to 50Mbps. We used the widely-used free-space propagation model [21] and the Shannon's theorem to derive the BS capacities on other channels. To avoid overloading caused by serving migrated traffic loads, we conservatively set the capacity of each BS to 80% of the calculated value.

We used Equation (1) to calculate power consumption of a BS. We followed the power consumption settings in [20]. Specifically, we set $A = 2100$W for each BS. The load coefficient B^f was set to 6 for the channel at $f = 2$GHz [20]. As described above this coefficient is channel dependent. B^f consists of two parts: the frequency dependent part $\hat{B}^f$ and the frequency independent part. The value of the frequency dependent part at frequency f can be calculated using the following equation:

$$\hat{B}^f = B^{2G}\gamma + B^{2G}(1-\gamma)\frac{\mu^{2G}}{\mu^f}, \tag{20}$$

where μ^f is the efficiency of the material at frequency f and γ is the percentage of channel dependent part, which was set to 0.51 according to [23]. We assumed that LMR-200 [25] is the material used for antenna and transmission line. Then μ^f can be obtained by using the attenuation and power handling calculator [26]. Using this equation, we can find out the values of B^f on different channels.

In all simulation scenarios, the total power consumption of BSs was used as the performance metric and the algorithm presented in Section IV-A was used for determining channel assignment. We used the Gurobi Optimizer 5.0 [7] to solve the MILP-Green to obtain optimal solutions (labeled as "Optimal"). Moreover, we compared our algorithm against a baseline algorithm which uses our algorithm for channel assignment but does not migrate loads or consolidate BSs. All the results presented in the following figures are average over 10 runs and in each run, a different seed was used for random generation of traffic loads.

In this first two scenarios, we evaluated the performance of the min-cost-flow-based algorithm (labeled as "Min-Cost-Flow") for the power-proportional case ($A_i = 0$). In scenario 1, we fixed the number of MVNO $K = 3$ and changed the number of BSs N from 30 to 80 with a step size of 10. In scenario 2, we fixed the number of BSs $N = 50$ and changed the number of MVNOs K from 1 to 6. In these two scenarios, the load of an MVNO on a BS followed a Gaussian distribution with a mean of 5Mbps and a variance of 1Mbps. The simulation results were presented in Figs. 2–3.

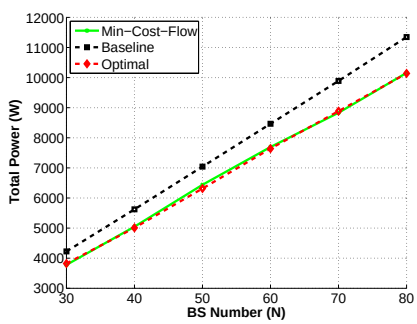

Fig. 2. Scenario 1: varying BS number (N), power-proportional

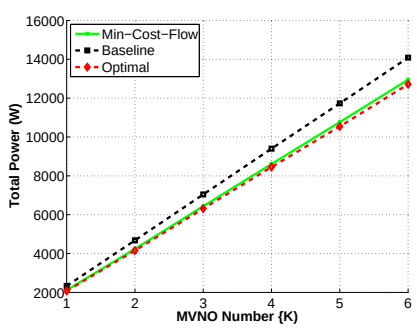

Fig. 3. Scenario 2: varying MVNO number (K), power-proportional

We can make the following observations from these results:

1) The proposed algorithm consistently outperforms the baseline algorithm. On average, it achieves 10% power savings. This shows that even for the power proportional case, migrating traffic loads to more power-efficient BSs can save power. Moreover, the proposed algorithm produces close-to-optimal solutions since it spends only 1% more power than the optimal on average.

2) No matter which algorithm was used, the power consumption increases linearly with the number of BSs and the number of MVNOs because of the linear power consumption model with $A_i = 0$.

In the next three scenarios, we evaluated the performance of the bilinear relaxation based algorithm (labeled as "Bilinear"), the iterative shutdown algorithm (labeled as "Iterative") and the joint algorithm (labeled as "Joint"). The simulation settings of scenarios 3 and 4 were the same as those of scenarios 1 and 2 respectively. We had an additional scenario, scenario 5, in which we fixed $N = 40$ and $K = 6$, and we changed the load of each BS from $10\% * l$ to $100\% * l$ with a step size of $10\% * l$, where l is the MVNO load on a BS generated using the method described above. The simulation results were presented in Figs. 4–6.

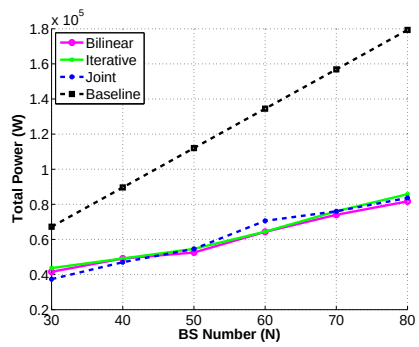

Fig. 4. Scenario 3: varying BS number (N), the general case

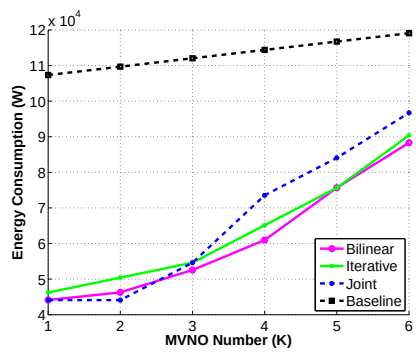

Fig. 5. Scenario 4: varying MVNO number (K), the general case

We can make the following observations from these results:

1) All the proposed algorithms perform similarly and they all significantly outperform the baseline algorithm. On average, the bilinear relaxation based algorithm, the iterative shutdown algorithm and the joint algorithm, achieve 47%, 46% and 45% power savings respectively, which are more significant than those in the power-proportional case. This show that BS consolidation via load migrations can save power significantly, which well justifies the motivation of this paper.

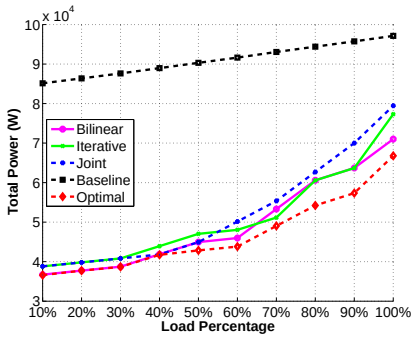

Fig. 6. Scenario 5: varying MVNO loads, the general case

2) From Fig. 6, we can see all the proposed algorithms yield close-to-optimal performance. Specifically, they spend only 4% more power than the optimal.

3) By increasing the number of BS, the number of MVNOs or MVNO loads (directly), we essentially increase the loads in the network. As expected, the total power consumption increases with the loads no matter which algorithm was used. However, an interesting observation is that the total power consumption does not increases linearly with the loads as what we observed in the power-proportional case. This shows that in the general case, significant power savings come from shutting down BSs because idle power contributes a significant portion of power consumption.

VII. Conclusions

In this paper, we considered a power-efficient network planning problem in virtualized CRNs First, we presented an MILP to provide optimal solutions. Then we presented a general optimization framework to guide algorithm design, which solves two subproblems, channel assignment and load allocation, in sequence. We presented a channel assignment algorithm with an approximation ratio of $(\frac{1}{\Delta})$. For load allocation, we presented a polynomial-time optimal algorithm for the power-proportional case as well as two effective heuristic algorithms for the general case. In addition, we presented a heuristic algorithm that jointly solve the two subproblems. It has been shown by simulation results that the proposed algorithms produce close-to-optimal solutions, and moreover, achieve over 10% and 45% power savings in the power proportional and general cases respectively, compared to a baseline algorithm that does not migrate loads or consolidate BSs.

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